

Article

Coupling Mechanism and Driving Paths of the Spatial Differentiation of Tourism Attractions from the Perspective of Tourist Perception—A Case Study of Xinjiang, China

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Abstract

As the culture and tourism industry moves toward high-quality development, tourist perception has become a core dimension for measuring that quality. Most existing work on tourism spatial differentiation still looks at the supply side, and describes the pattern of tourism attractions. It pays limited attention to how supply and demand couple with each other, and it offers little systematic evidence from large-scale, highly heterogeneous regions. This study combines multi-source tourism point data with review texts from Trip.com (hereafter, Trip) and Rednote (Xiaohongshu). Using RoBERTa-wwm, a pretrained Chinese language model with whole-word masking, together with a coupling-coordination model and the geographical detector, we analyze how the spatial differentiation of tourism attractions couples with tourist perception, and we trace the driving mechanism to land resources, tourism resources and socioeconomic conditions. The results show that tourist sentiment perception in Xinjiang forms a spatial pattern that is led by core cities and declines outward layer by layer, and the coupling coordination between the distribution of tourism attractions and tourist sentiment perception remains higher in the north and lower in the south. The two systems do not, however, follow a simple linear relation: infrastructure coverage emerges as the strongest correlate of coordination, whereas regional economy and population size explain it only weakly. This study therefore extends the demand-side perspective in research on tourism spatial differentiation, and it offers a scientific basis and a decision-making reference for large-scale regions that seek to optimize tourism spatial layout and to upgrade the industrial quality.



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1. Conceptual Clarification and Theoretical Framework

Tourist perception is the multidimensional psychological process through which tourists select, organize and interpret stimuli such as the environment, the services and the culture of a destination or an attraction, in a specific tourism context. It is situational

and subjectively constructed, and it operates on three levels, namely, cognitive evaluation, emotional response and behavioral intention [1]. Tourism scholars frequently use tourist perception alongside tourist experience, satisfaction and sentiment, yet the four concepts have distinct theoretical boundaries. Tourist experience denotes the overall course and the subjective feelings of tourists before, during and after a visit, so it covers perception, emotion, memory and meaning construction [2,3]. Satisfaction refers to the gap evaluation that tourists form when they compare an actual experience with their prior expectations, which makes it a cognitive judgment reached after the visit, and the expectancy disconfirmation model provides its classic measurement framework [4,5]. Sentiment refers to the positive, neutral or negative valence that reviewers express in their texts, and it forms a measurable subset of the emotional dimension of tourist perception, rather than perception as a whole [6,7]. What we extract from online review texts with the RoBERTa-wwm model is the sentiment valence dimension of tourist perception, and we treat it as a proxy for the overall level of tourist perception. This measurement does not capture the cognitive dimension, such as specific evaluations of landscape quality, and it does not capture the behavioral intention dimension, such as revisit and recommendation intention. The interpretation of the conclusions, therefore, should stay within the level of sentiment perception.

Place theory further links tourist perception to place image, place identity and place reputation [8]. Place image refers to the sum of the beliefs, impressions and emotions that tourists hold toward a destination or an attraction, so it projects and condenses tourist perception at the place level. Place identity refers to the emotional bond and the sense of meaning attachment that develops between the self-concept of tourists and a place, which makes it the internalized product of perception after deep experience. Place reputation, refers to the public image that emerges once the evaluations of tourists, residents, media and official agencies converge, and it is therefore a socially constructed form of collective perception [9,10]. The three concepts form a progression that runs from individual perception to collective image, and tourist perception serves as the starting point and micro foundation of that. Perception does not arise in isolation. It takes shape through the interaction among place image, prior expectation, past experience and immediate impression. Place image and prior expectation shape the perceptual frame that tourists bring to a site, past travel experience supplies the reference benchmark, and immediate impressions, in turn, update place image and future expectations, which creates a recurring feedback loop [11]. The tourist sentiment perception that we capture with cross-sectional data is a snapshot of this process at one point in time, and our conclusions describe the association between tourist perception and the spatial pattern of attractions within a specific time window. Setting out these boundaries and relationships helps readers interpret the empirical findings precisely, and it guards against reading measured sentiment valence as a comprehensive account of overall tourist perception, tourist satisfaction or place image.

2. Literature Review

Driven by the integration of culture and tourism and by the strategy of expanding domestic demand, tourism has become an important engine of industrial convergence, urban–rural coordination, and regional branding [12]. Tourism attractions are the core units of tourism supply and the spatial foundation of tourist behavior, and the quality of their development, construction, operation and maintenance determines the development level and the comprehensive benefits of regional tourism [13]. Attractions nevertheless differ sharply in development stage, resource type, service capacity and market popularity, and a homogeneous approach to development and operation can no longer match such diversified demands [14]. Precise development and refined maintenance that follow the

observed patterns of spatial differentiation have therefore become a key issue for unlocking regional tourism potential and optimizing tourism spatial layout [15,16].

Researchers in China and elsewhere have built a multi-dimensional and systematic framework around tourism attractions, and this work falls into four brand strands [17]. The first strand examines spatial differentiation and pattern evolution. As a classic topic in tourism geography, it takes administrative or geographical units as its scope and applies spatial econometric methods such as kernel density estimation, spatial autocorrelation analysis and the geographic concentration index. These studies characterize the distribution, the agglomeration and the temporal evolution of attractions, and they pay particular attention to how resource endowment, transport location, socioeconomic level and policy orientation drive differentiation [18–20]. A second strand turns to tourism resource allocation and development efficiency. It builds evaluation systems that measure regional resource endowment and applies data envelopment analysis and coupling-coordination models to quantify how efficiently tourism resources are developed, used and converted into benefits. Work in this strand also addresses insufficient development, supply–demand mismatch and low utilization efficiency, and it proposes paths for optimizing allocation [21–23]. Operation management and sustainable development form a third strand, which covers the environmental carrying capacity of attractions, innovation in operation and maintenance models, the integrated development of culture and tourism, and ecological protection mechanisms. Its aim is to identify the balance among economic, social and ecological benefits, and thereby support sustainable operation [24–26]. The fourth strand evaluates tourist experience and service quality, and it has become a research hotspot as the experience economy deepens and mass tourism demand upgrades. Scholars here start from tourist demand and perception, construct evaluation systems that span service facilities, landscape quality and emotional value, and combine online reviews with travel blogs to uncover the core influencing factors and formation mechanisms of experience, which provides market-oriented references for service improvement and product iteration at attractions [27–30].

Questionnaire surveys and field interviews have long been the mainstream way of collecting data on tourist demand and perception, and they have produced a relatively mature quantitative paradigm [31]. Researchers typically distribute structured questionnaires on-site, add semi-structured interviews, and construct tourist perception evaluation systems around landscape quality, infrastructure, service level, transport accessibility, and cultural presentation [32,33]. Importance–performance analysis, structural equation modeling, multiple regression, and fuzzy comprehensive evaluation then help them identify the core drivers of tourist satisfaction [34,35] and trace the link between tourist demand preferences and revisit or recommendation intention [36]. Such surveys methods capture the subjective cognition and the psychological feelings of tourists precisely and reveal the logic behind an experience, so they support micro-level decisions about service optimization [37]. Survey costs and field conditions, however, keep sample sizes small and spatiotemporal coverage narrow, which makes it difficult to describe how tourist experience varies across numerous tourism attractions of large-scale regions [38].

The integration of Web 2.0 technology with the online tourism industry has turned user-generated content into an important carrier of authentic tourist perception and evaluation, and it has moved experience research into a big-data stage [39,40]. Platforms such as Trip, Meituan, Mafengwo, and Dianping have accumulated large volumes of reviews, travel blogs, consumption evaluations, and check-in records. These data are non-intrusive, large in sample size, broad in spatiotemporal coverage and highly timely, and they reproduce the immediate feelings and the overall evaluations of tourists across the whole travel process, which compensates for many limitations of traditional surveys [41–43]. Researchers now

apply natural language processing, sentiment analysis, latent Dirichlet allocation topic modeling and social network analysis [44,45] to extract the core dimensions, the emotional trajectories and the attention hotspots of tourist experience from large text corpora, and they also test how far tourist perception matches the supply of tourism attractions [46,47]. Most of this work, nevertheless, evaluates the experience quality at a single tourism attraction or within a small area, and few studies place the spatial characteristics of tourist experience and the overall differentiation pattern of tourism attractions in one coupling framework [48,49]. Research that explains the spatial differentiation of attractions from the perspective of tourist perception therefore remains thin.

This study addresses that gap. Taking Xinjiang as a case, we place tourist experience and the spatial differentiation pattern of tourism attractions in a single coupling framework. We first measure the sentiment score of each attraction from user reviews on online travel platforms and map the spatial differentiation of tourist sentiment perception. We then build a measurement system for the spatial differentiation of attractions and apply the coupling-coordination model to quantify how far the two dimensions develop in step, which identifies spatial matching differences and mismatch problems. We finally screen the core influencing factors, clarify the coupling mechanism between the two dimensions, and propose corresponding optimization paths.

3. Materials and Methods

3.1. Study Area

We take the Xinjiang Uygur Autonomous Region of China as the case area (Figure 1). As cultural and tourism integration has advanced and tourism infrastructure has improved, the tourism market of Xinjiang has grown rapidly, and the region received 323 million tourist visits in 2025. Visitor numbers and industrial returns have risen for several consecutive years, which makes Xinjiang one of the core areas driving domestic tourism growth [50]. This large volume of visitors has also left abundant reviews, travel notes and consumption evaluations on mainstream online travel platforms such as Trip, Mafengwo and Meituan. The resulting user-generated content is large in scale and wide in coverage, so it supplies ample samples for quantitative research from the perspective of tourists. Tourism attractions in Xinjiang are, moreover, spread across a vast area and differ markedly in type; their spatial differentiation is pronounced, and tourist experience quality varies clearly, across regions. Xinjiang, therefore, serves as a typical area for examining how the spatial differentiation of tourism attractions couples with tourist perception.

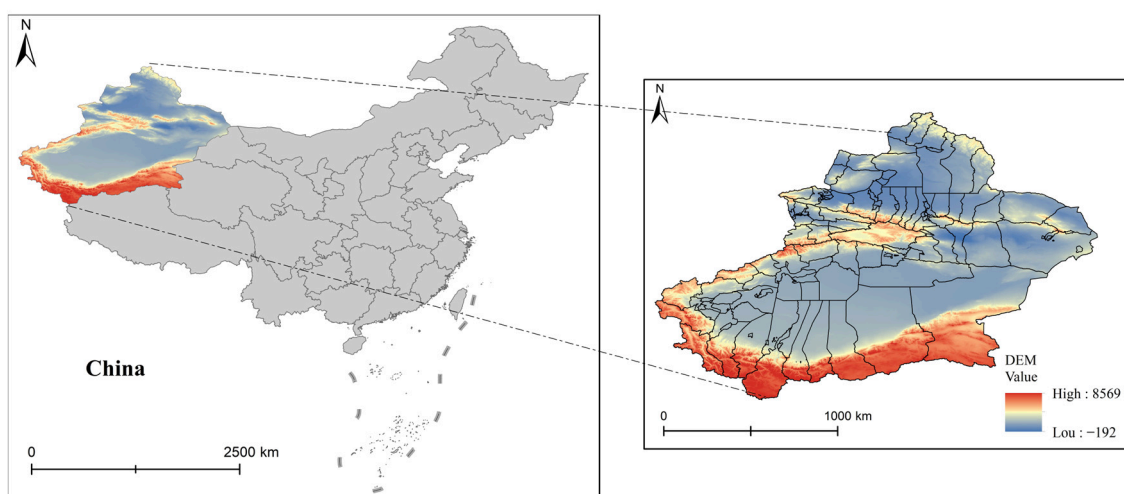


Figure 1. Study area.

3.2. Study Data

3.2.1. Distribution Data of Tourism Attractions

The attraction data used here consist of two parts, namely the official A-level scenic area data and the popular check-in spot data from online platforms, which together cover tourism space carriers of different levels and types. The A-level scenic area data come from the lists released by the Ministry of Culture and Tourism and by the Department of Culture and Tourism of the Xinjiang Uygur Autonomous Region, and they include all 3A, 4A and 5A scenic areas in the region. Because these lists follow unified identification standards and standardized attribute information, they are authoritative and horizontally comparable, and they form the core of the regional tourism attraction system [51]. The check-in spot data come from Rednote and Trip, two mainstream culture and tourism platforms, and we collected them by retrieving information on popular tourism spots within Xinjiang. They supplement the emerging internet-famous attractions and the niche sites that official lists omit, so they track the actual travel choices of current tourists more closely, and give a fuller picture of the real supply of tourism attractions in Xinjiang [52]. We processed the data in three steps. We first sorted the official lists, extracted core attributes such as name, grade and administrative affiliation, and geocoded each scenic area to obtain its longitude and latitude. We then cleaned the raw check-in data from Rednote and Trip, removed duplicate spots, purely commercial venues and non-tourism information, and retained the valid tourism spots that attract a certain level of tourist attention. Finally, we verified the names of the two kinds of data and merged them after deduplication, unified the coordinate system, and added attribute fields such as attraction type and prefecture. These procedures produced a spatial dataset of tourism attractions in Xinjiang that covers different levels and diverse types, and that provides the basic research units for the analysis of spatial differentiation below (Figure 2).

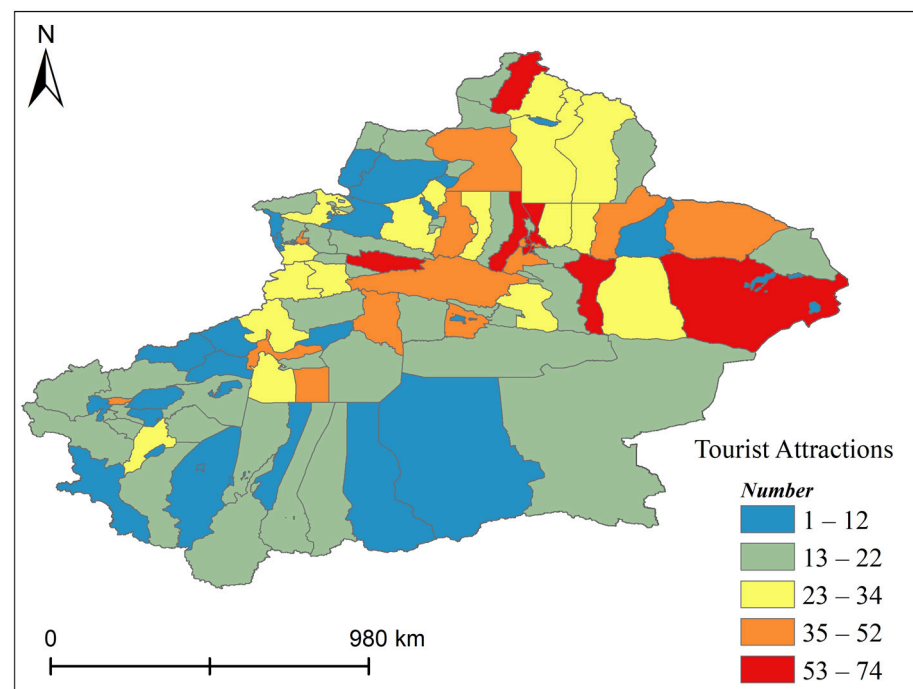


Figure 2. Distribution data of tourism attractions.

3.2.2. Tourist Perception Data

The tourist perception data come from Trip and Rednote. The two platforms complement each other in content attributes and coverage scenarios, so together they map

the real experience of tourists at different types of tourism attractions [53]. Trip is a mature online travel booking and review platform, and its reviews mostly concern formal A-level scenic areas. They focus on core sightseeing elements such as landscape quality, ticketing service, supporting facilities and traffic accessibility, and their structured and clearly oriented content reflects the overall experience of tourists at traditional attractions. Rednote is a lifestyle sharing platform, and the travel notes and check-in comments of its users cover not only A-level scenic areas, but also many internet-famous attractions and niche destinations. This content carries a stronger sense of scene and emotion, so it supplements the perception information of emerging tourism spots and matches the research samples of all types of tourism attractions. The data processing involved two steps: namely, collection, and cleaning with standardization. Using the established list of tourism attractions as the retrieval basis, we matched keywords such as attraction name and prefecture, collected the user review texts and public notes published on the two platforms in 2025, and extracted associated fields including posting time, user rating and spatial location. We then cleaned the raw data, removed duplicate content, commercial advertisements, invalid spam and records with incomplete information, unified the text encoding format, and applied word segmentation to delete stop words and meaningless symbols, so that only valid texts recording tourism experience remained. These procedures produced a tourist perception dataset covering the main tourism attractions in Xinjiang.

The final dataset has the following basic features. The two platforms together yielded 128,560 raw comments and notes. After we removed duplicates, commercial advertisements and meaningless filler content, and filtered out incomplete records, 86,420 valid review texts remained, which gives a retention rate of 67.2%. Trip contributed 51,380 valid comments, or 59.5% of the total, and Rednote contributed 35,040 valid notes, or 40.5%, so the two sources complement each other in content attributes and in the scenarios they cover. The valid samples cover 326 tourism attractions and involve 14 prefectures and prefecture-level cities, as well as 86 county-level research units. Core tourism areas rank at the top in sample size, and Urumqi, the Ili Kazakh Autonomous Prefecture and the Kashgar Prefecture account for 18.5%, 16.2% and 12.8% of all valid samples, respectively, followed by the Altay Prefecture, the Bayingolin Mongol Autonomous Prefecture and Turpan with shares of 9.6%, 8.3% and 7.1%. The peripheral counties of southern Xinjiang and the remote pastoral areas of northern Xinjiang hold much lower shares, so the sample distribution largely matches the spatial pattern of tourist flows. To secure the statistical reliability of the tourist perception score of each attraction, we set a minimum threshold of 30 valid comments: 214 attractions, or 65.6% of those covered, passed this screening and entered the coupling-coordination analysis. Section 3.3.2, on multi-scale data aggregation, explains in detail how the sentiment score of a single review moves up to the attraction level, and further, to the county level, along with the weighting scheme behind each step.

3.2.3. Data of Influencing Factors

To analyze the driving mechanism behind the coupling between the spatial differentiation of tourism attractions and tourist perception, we selected eight core indicators from three dimensions, namely, the land resource base [54,55], tourism industry development [56,57] and socioeconomic support [58,59], and used them to build a driving-factor system. All data come from authoritative open databases and official statistical materials, and spatial alignment, quantitative measurement and standardization turned them into a driving-factor dataset that matches the research units precisely.

The land resource base contains three indicators, namely, relief degree of land surface (RDLS), the fragmentation of tourism resources (FTR) and the climate comfort index (CCI), which describe how natural geographical conditions constrain the spatial pattern of tourism

attractions and tourist perception. RDLS relies on digital elevation model (DEM) data released by the Geospatial Data Cloud. FTR builds on the spatial dataset of tourism attractions described above, and we measured it with the aggregation index (AGI) among the landscape pattern metrics, so that it quantifies the clustering and dispersion features of tourism resources across Xinjiang. CCI draws on the surface meteorological observation records of the China Meteorological Data Service Centre, and we combined the temperature–humidity index (THI) with the wind-effect index (WEI) to calculate the annual duration suitable for sightseeing in each region, which captures the underlying influence of climate on the quality of tourist experience.

Tourism industry development covers three indicators, namely, the intensity of tourism development (ITD), the richness of tourism format (RTF) and infrastructure coverage (IC), which focus on how the supply-side drives spatial differentiation and experience quality. We measured ITD as a weighted composite of attraction density and tourist arrivals, drawing on statistical bulletins from the regional Department of Culture and Tourism and on prefecture-level annual tourism reports, so the indicator captures both the depth of resource exploitation and the scale of industrial development. RTF builds on the points of interest (POI) of Amap and on the business format information of online culture and tourism platforms. We counted the types and the numbers of tourism-related formats within each region, including catering, accommodation, leisure and entertainment, and cultural experience, which reflects how diversified the supporting tourism supply is. IC draws on road network density and on the coverage of public service facilities, both taken from OpenStreetMap, and it captures the capacity of local transport and basic public services to support tourism.

Socioeconomic support contains two indicators, namely, the economic development level (EDL) and population density (PD), which reflect how the macro socioeconomic environment supports tourism development. We characterized EDL with the per capita gross regional product (GRP) at the county and prefecture level, and we calculated PD as the number of permanent residents per unit of administrative area. Both come from the *Xinjiang Statistical Yearbook* and from the county-level materials of the national population census, and, together, they indicate the local source market and the consumption potential of each region. We matched all indicator data to spatial research units of the same scale and applied range standardization to remove dimensional differences, which provides a standardized variable basis for the spatial econometric analysis of the coupling driving mechanism below.

For transparency and reproducibility, we describe the calculation process, the spatial scale and the data year of the eight indicators, in a unified way. All indicators are matched to county-level spatial research units, and part of the prefecture-level data is allocated to the corresponding counties, according to administrative boundaries. The data year is mainly 2024, whereas the tourism reception volume and the attraction data come from 2025, and all indicators enter the factor-detection analysis after range standardization.

We calculated the eight indicators as follows. (1) RDLS relies on DEM data with a resolution of 30 m. We used a 7×7 window of roughly $210 \text{ m} \times 210 \text{ m}$, calculated the difference between the highest and the lowest elevation within each window, and took the mean of all window differences within a county to represent the degree of regional terrain relief, so the formula is $RDLS = \text{mean} (H_{\max} - H_{\min})$. (2) FTR relies on the spatial dataset of tourism attractions. We divided each county into a $1 \text{ km} \times 1 \text{ km}$ grid, treated every grid cell as a patch unit, calculated AGI among the landscape pattern metrics, and took its reverse value to represent the degree of fragmentation, so the formula is $FTR = 1 - AI$ and the value ranges from 0 to 1. A larger value indicates that tourism resources scatter more widely in space. (3) CCI relies on ground meteorological observation

data. We calculated the THI as $THI = T - 0.55 \times (1 - RH) \times (T - 14.5)$ and the WEI as $WEI = -(10\sqrt{V} + 10.45 - V) \times (33 - T) + 8.55S$, where T denotes the monthly mean air temperature in $^{\circ}\text{C}$, RH denotes the monthly mean relative humidity in %, V denotes the monthly mean wind speed in m/s , and S denotes the monthly mean sunshine duration in h/d . We treated a day as comfortable when THI falls between 15 and 27 and WEI falls between -200 and -80 , and we then counted the number of comfortable travel days per year, with the unit of days per year. (4) ITD combines two sub-indicators, namely, the number of scenic areas per unit area and the tourism reception volume. We first standardized them by the range method and then summed them with weights of 0.4 and 0.6, so the formula is $ITD = 0.4 \times \frac{\frac{N_i}{A_i}}{(\frac{N}{A})_{\max+0.6}} \times \frac{\frac{T_i}{A_i}}{(\frac{T}{A})_m}$, where N_i denotes the number of scenic areas in a county, T_i denotes the tourism reception volume of the county, and A_i denotes the administrative area of the county, and the result is a dimensionless index. (5) RTF relies on the POI data of Amap. We counted the number of business format types within a county across four major tourism-related categories, namely catering, accommodation, leisure and entertainment, and cultural experience, and then measured diversity with the Shannon index, so the formula is $RTF = -\sum(p_k \times \ln[p_k])$, where p_k denotes the share of the POI number of the k -th category in the total of the four categories, and the result is a dimensionless index. (6) IC combines two sub-indicators with equal weights, namely road network density and the coverage share of public service facilities, so the formula is $IC = 0.5 \times \frac{\frac{L_i}{A_i}}{(\frac{L}{A})_{\max+0.5}} \times (\frac{F_i}{F_{\text{total}}})$, where L_i denotes the total road mileage of a county and includes expressways, national roads, provincial roads and county roads, and F_i denotes the share of the area covered by public service facilities in the county, which include medical institutions, schools, commercial outlets and tourist service centers, and the result is a dimensionless index. (7) EDL uses the per capita GRP of a county, so the formula is $EDL = \frac{GDP_i}{P_i}$ and the unit is yuan per person. (8) PD uses the ratio of the permanent-resident population of a county to its administrative area, so the formula is $PD = \frac{P_i}{A_i}$ and the unit is persons per km^2 .

Before the indicators entered the geographical detector analysis, we applied the range standardization to remove differences in dimension. For positive indicators, whose larger values contribute more strongly to coupling coordination, the standardization formula is $x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$. For negative indicators such as FTR, whose higher values indicate that resources scatter more widely and therefore hinder coordinated development, the standardization formula is $x' = \frac{x_{\max} - x}{x_{\max} - x_{\min}}$. After standardization, all indicators fall within the range from 0 to 1. Table 1 summarizes the definition, the unit, the data source, the year, the spatial scale and the calculation process of the eight driving factors.

Table 1. Indicator system and measurement description of the driving factors.

Dimension	Variable	Abbreviation	Definition and Formula	Unit	Data Source	Year	Spatial Scale
Land resource base	Relief degree of land surface	RDLS	Mean elevation difference within a 7×7 window based on DEM	m	Geospatial Data Cloud (SRTM 30 m DEM)	2020	County
Land resource base	Fragmentation of tourism resources	FTR	1 minus the aggregation index (AGI), measured with attraction patches on a $1 \text{ km} \times 1 \text{ km}$ grid	Dimensionless	Spatial dataset of tourism attractions built in this study	2025	County
Land resource base	Climate comfort index	CCI	Number of comfortable travel days per year, judged jointly by the temperature humidity-index (THI) and the wind-effect index (WEI)	Days per year	China Meteorological Data Service Centre (ground meteorological observation data)	Mean of 2020 to 2024	County (station interpolation)
Tourism industry development	Intensity of tourism development	ITD	$0.4 \times$ standardized density of scenic areas plus $0.6 \times$ standardized density of tourist arrivals	Dimensionless	Statistical bulletin of the Department of Culture and Tourism of the Xinjiang Uygur Autonomous Region	2025	Prefecture-level data allocated to counties

Table 1. Cont.

Dimension	Variable	Abbreviation	Definition and Formula	Unit	Data Source	Year	Spatial Scale
Tourism industry development	Richness of tourism formats	RTF	Shannon diversity index covering catering, accommodation, leisure and entertainment, and cultural experience	Dimensionless	Amap POI data and business-format information from online culture and tourism platforms	2025	County
Tourism industry development	Infrastructure coverage	IC	$0.5 \times \text{standardized road network density} + 0.5 \times \text{standardized coverage share of public service facilities}$	Dimensionless	OpenStreetMap (road network and facility data)	2024	County
Socioeconomic support	Economic development level	EDL	Per capita GRP, that is total GRP divided by permanent-resident population	Yuan per person	<i>Xinjiang Statistical Yearbook</i>	2024	County
Socioeconomic support	Population density	PD	Permanent-resident population divided by administrative area	Persons per km ²	<i>Xinjiang Statistical Yearbook</i> and county-level data of the Seventh National Population Census	2024	County

3.3. Methods

3.3.1. Coupling-Coordination Model

The coupling-coordination model derives from coupling theory in physics. It describes two or more complex systems that maintain a two-way feedback relationship, and it quantifies both the strength of their interaction and the quality of their coordinated development [60]. Applied to the relationship between the spatial differentiation of tourism attractions and tourist perception, the model identifies the spatial matching degree, the synergy level and the mismatch type of the two systems, which supports the later analysis of driving mechanisms and the design of differentiated optimization paths. The model has three advantages over correlation analysis, regression modeling and the spatial mismatch index, which tourism research commonly uses. It captures two-way and nonlinear feedback, rather than one-way causation, whereas regression analysis and correlation analysis only verify the strength of linear influence or the direction of association among variables, and they assume by default that independent variables act on dependent variables in one direction, so they cannot reflect the two-way interaction between the spatial differentiation of tourism attractions and tourist perception. Second, it separates coupling intensity from development level, whereas a conventional matching index reports only the numerical gap between two systems. and cannot distinguish a well-coordinated pair at a low development level from a poorly coordinated pair at a high one. Third, and finally, it works at any spatial granularity, since it runs on counties or prefectures alike, and returns both a coordination grade and a mismatch direction for each unit, which supports region-specific diagnosis, rather than a single averaged conclusion [61]. The model is formulated as follows.

(1) Measurement of the comprehensive development index of each system

This study first builds an evaluation index system for each of the two subsystems, namely the spatial differentiation of tourism attractions and tourist perception. The former comes from a weighted sum of multidimensional indicators, whereas the latter is a single indicator system that takes the tourist sentiment perception score aggregated at the county level as its core indicator, and the aggregation method appears in Subsection 6 of Section 3.3.2. After range standardization, this score serves directly as the comprehensive development index of the tourist perception subsystem. The general form for calculating the comprehensive development index of each system is as follows.

$$U_i = \sum_{j=1}^n w_j \cdot x'_{ij}$$

where U_i is the comprehensive evaluation value of the i th system, w_j is the weight of the j th indicator, and x'_{ij} is the standardized value of the j th indicator in the i th system, whose range falls within $[0,1]$.

(2) Coupling degree

The coupling degree measures how strongly the two systems interact with each other.

$$C = \left\{ \frac{U_1 * U_2}{\left(\frac{U_1 + U_2}{2}\right)^2} \right\}^k$$

where C is the coupling degree, and its range falls within $[0,1]$. A larger C value indicates that the two systems interact more strongly, and that their coupling relationship grows closer. k is the adjustment coefficient, and researchers generally set it to 2 for the coupling of two systems.

(3) Coupling-coordination degree

The coupling-coordination degree accounts for both the interaction intensity and the overall development level of the two systems, so it serves as the core indicator of the quality of coordinated development.

$$D = \sqrt{C * TT} = \alpha U_1 + \beta U_2$$

where D is the coupling-coordination degree and its range falls within $[0,1]$. A larger D value indicates that the two systems reach a higher level of coordinated development. T is the comprehensive development index, which reflects how the overall development level of the two systems contributes to the coordination degree. Furthermore, α and β serve as the weight coefficients of the two systems. Because the spatial differentiation of tourism attractions and tourist perception support each other and carry equal importance here, we set $\alpha = \beta = 0.5$.

3.3.2. RoBERTa-wwm Model

Quantifying tourist perception is the core premise of the coupling-coordination analysis. The RoBERTa-wwm model extracts the sentiment valence of tourist evaluations from review texts, and classifies it as positive, neutral or negative. We treat this output as a quantitative proxy for the sentiment dimension of tourist perception, rather than a full measurement of perception, which would also cover cognitive evaluation and behavioral intention, and the findings below should be read at the level of sentiment perception, accordingly. We applied the model to the unstructured review texts collected from Trip and Rednote, in order to identify sentiment orientation and to measure experience intensity. This step turns subjective textual reviews into computable numerical indicators, and it thus provides the core data support for the comprehensive evaluation of the tourist perception subsystem based on sentiment scores and for the analysis of its spatial differentiation [62]. Compared with sentiment lexicons, naive Bayes classifiers and the original Bidirectional Encoder Representations from Transformers (BERT) model, RoBERTa-wwm reaches higher accuracy in Chinese semantic understanding, and fits the complex expressions of tourism settings better. Whole-word masking matches the characteristics of written Chinese, because it masks complete words rather than single characters during pretraining, and thereby overcomes the tendency of character-level masking to ignore the semantics of a whole word. As a result, the model recognizes colloquial expressions, internet buzzwords, negative sentence patterns and implicit sentiment tendencies in tourism texts, and it adapts well to the markedly different language styles of Rednote and Trip [63,64].

The model takes the Transformer encoder as its core architecture, and acquires deep semantic representation through unsupervised pretraining on a large corpus. After domain

fine-tuning on the tourism sentiment analysis task, it quantifies textual sentiment precisely. The core computation proceeds in three steps.

(1) Semantic embedding in the input layer.

The model first converts the input text into vector representations. The input embedding is the sum of the word embedding, the position embedding and the segment embedding, as the following equation shows.

$$H_o = E_w + E_p + E_s$$

where H_o is the initial input vector of the model, E_w is the word-embedding vector, which carries the semantic information of each character or word, E_p is the position-embedding vector, which carries the positional information of a word within the text, and E_s is the segment-embedding vector, which distinguishes different text segments.

(2) Semantic extraction in the Transformer encoding layer.

The input vector then passes through the attention mechanism of several layers of bidirectional Transformer encoders, which capture the contextual semantic associations of the text, and output its global semantic features. We take the output vector H that corresponds to the special token at the first position of the sequence as the overall semantic representation of a review text, and we use this vector for the subsequent sentiment classification.

(3) Sentiment probability computation in the output layer.

For the tourism sentiment classification task, we attached a fully connected layer and a Softmax activation function to the top of the pretrained model. Together, they map the global semantic features onto a probability distribution over the sentiment categories, as the following equation shows.

$$p_i = \text{Softmax}(W \cdot H + b) = \frac{e^{W_i \cdot H + b_i}}{\sum_{k=1}^n e^{W_k \cdot H + b_k}}$$

where p_i is the predicted probability that the text belongs to the i th sentiment category, n is the total number of sentiment categories, which we set to three, namely positive, neutral and negative, and W and b denote the weight matrix and the bias term of the fully connected layer, which fine-tuning updates and optimizes.

To adapt the pretrained model to tourism settings, we fine-tuned the RoBERTa-wwm model on manually annotated tourism-review samples. We drew 6000 texts from the 86,420 valid reviews by stratified random sampling, which took account of the platform source, where Trip and Rednote followed a ratio of roughly 6 to 4, and of the spatial representativeness of the attractions. Two annotators with a professional background in tourism management labeled every text independently as positive, neutral or negative. The Cohen kappa coefficient for inter-annotator consistency reached 0.82, and a third senior researcher arbitrated the disputed samples, which produced a consistent annotation dataset. The annotated samples comprise 3912 positive texts (65.2%), 1188 neutral texts (19.8%) and 900 negative texts (15.0%), a distribution typical of tourism reviews, in which positive evaluations dominate. We then split the dataset randomly into a training set of 4800 texts, a validation set of 600 texts and a test set of 600 texts in a ratio of 8 to 1 to 1, and the split kept the proportion of each category constant.

Fine-tuning used the following key hyperparameters. The optimizer was AdamW, the initial learning rate 2×10^{-5} , the weight decay coefficient 0.01 and the learning rate warmup ratio 10%. We set the batch size to 16, the maximum sequence length to 256 and the number of training epochs to 4, and an early stopping strategy monitored the validation

loss, with a patience value of 2. Training ran on a single NVIDIA RTX 3090 GPU, where one training epoch took about 18 min and the whole training process took about 75 min.

Table 2 reports the performance of the model on the test set. Overall accuracy reaches 89.3%, macro-averaged precision (macro-P) 86.7%, macro-averaged recall (macro-R) 85.1% and the macro-averaged F1 score (macro-F1) 85.9%. The model identifies positive sentiment best, with precision, recall and F1 of 92.5%, 93.8% and 93.1%, respectively, while the F1 score reaches 81.2% for the neutral category and 83.4% for the negative category. Domain fine-tuning, therefore, yields accurate sentiment classification and good generalization, which gives a reliable basis for measuring tourist perception scores.

Table 2. Classification performance of the RoBERTa-wwm model on the test set.

Sentiment Category	Precision	Recall	F1 Score	Number of Samples
Positive	92.5%	93.8%	93.1%	391
Neutral	80.6%	81.8%	81.2%	119
Negative	87.1%	79.8%	83.4%	90
Macro/average	86.7%	85.1%	85.9%	—
Overall accuracy	—	—	89.3%	600

(4) Measurement of the comprehensive sentiment score.

To match the dimensional requirements of the indicator system in the coupling-coordination model, and to follow the 0–100 scale conventional in tourism evaluation, we weighted the predicted probabilities of the three sentiment categories and mapped tourist sentiment orientation linearly onto a continuous score within the interval from 0 to 100, as the following equation shows.

$$S = 100 * (p_1 * 1 + p_2 * 0.5 + p_3 * 0)$$

where S is the composite sentiment score of a single review text, and its value ranges from 0 to 100, while p_1 , p_2 and p_3 correspond to the predicted probabilities of positive, neutral and negative sentiment, respectively, and satisfy $p_1 + p_2 + p_3 = 1$. A score closer to 100 indicates stronger positive sentiment toward the experience at an attraction, a score around 50 indicates generally neutral sentiment, and a score closer to 0 indicates that negative perception becomes more prominent.

The weights of 1 for positive sentiment, 0.5 for neutral sentiment and 0 for negative sentiment rest on three grounds. The first ground is theoretical. In the valence dimension of emotion psychology, the sentiment expressed in tourist-review texts forms a continuous spectrum whose core axis runs between satisfaction and dissatisfaction. Positive sentiment corresponds to recognition of the travel experience and willingness to recommend it, negative sentiment corresponds to dissatisfaction and a tendency to complain, and neutral sentiment lies between the two, and indicates that tourists have formed no clear judgment; an intermediate weight of 0.5 accords with the hierarchical logic of sentiment valence. The second ground is consistency with mainstream platform-rating systems. Platforms such as Trip generally use a five-star scale, on which three stars denote an average and neutral evaluation. Mapped onto a range from 0 to 100, three stars fall close to 50 points, which matches the neutral weight of 0.5, while five stars and one star fall at the high end and the low end of the range, and confirm the gradient between the weights. The third ground is empirical. We tested the correlation between the composite sentiment score that the model outputs and the original five-star user ratings on Trip. The Pearson correlation coefficient reaches 0.81 ($p < 0.001$), and the Spearman rank correlation coefficient reaches 0.78 ($p < 0.001$), which shows that the composite score reproduces the real evaluation tendency

of tourists, and holds good empirical validity. The 0–100 form also allows the score to be standardized, together with the multidimensional indicators of the attraction differentiation system, which safeguards the rationality of the coupling-coordination measurement.

(5) Multi-scale data aggregation method

The comprehensive sentiment score of a single review has to pass through three levels of aggregation, from review to attraction and then to spatial unit, before it turns into the county-level tourist perception indicator required by the coupling-coordination analysis. To keep the whole process transparent and reproducible, this study states the calculation method, the weighting scheme and the screening rule of each level, as follows.

Level one covers the aggregation from a single review to the attraction level. For the same attraction, this study aggregates reviews within each platform first and then combines the platform results into a final score for the attraction. Specifically, for all valid reviews of attraction j on platform p (p belongs to Trip and Rednote), the arithmetic mean gives the sentiment score of this attraction on that platform, which means every review carries equal weight, and no adjustment follows from review length or user profile.

$$S_{j,p} = \frac{1}{n_{j,p}} \sum_{i=1}^{n_{j,p}} s_i$$

where $S_{j,p}$ denotes the average sentiment score of attraction j on platform p , $n_{j,p}$ denotes the number of valid reviews of this attraction on platform p , and s_i denotes the comprehensive sentiment score of the i th review. On this basis, the cross-platform synthesis takes an equally weighted average, so Trip and Rednote each receive a weight of 50 percent.

$$S_j = \frac{S_{j,\text{trip}} + S_{j,\text{rednote}}}{2}$$

The reason for choosing an equally weighted average instead of a weighting by review number lies in the systematic difference between Trip and Rednote in user profile and content attribute, since reviews on Trip are highly structured and clearly targeted, while content on Rednote carries a stronger sense of scene and emotion. If the synthesis followed review numbers, the evaluation preference of Trip users would dominate the score of an attraction, and would weaken the complementarity of the two platforms, whereas equal weighting lets the perspectives of both platforms contribute in a balanced way to the final score. When an attraction holds valid reviews on only one platform, the mean of that platform directly becomes the score of this attraction. In addition, to secure the statistical reliability of the score of a single attraction, this study sets a minimum threshold for review quantity, and only an attraction with no fewer than 30 valid reviews across the two platforms enters the subsequent analysis. After this screening, 214 attractions finally enter the aggregation process.

Level two covers the aggregation from attractions to county-level spatial units. This study takes the county as the basic spatial unit of the coupling-coordination analysis. For a county k that contains several qualified attractions, the tourist sentiment perception score of this county comes from a weighted average based on the review number of each attraction.

$$S_k = \frac{\sum_{j \in k} S_j \times n_j}{\sum_{j \in k} n_j}$$

where S_k denotes the tourist sentiment perception score of county k , S_j denotes the sentiment score of the j -th attraction within that county, and n_j denotes the total number of valid cross-platform reviews that this attraction has received. We weight the aggregation by review volume instead of taking a simple arithmetic mean because attractions with

larger review volumes yield more robust sentiment estimates and correspondingly smaller standard errors. Weighted aggregation thus reduces the influence that the score fluctuations of small-sample attractions exert on the county mean, and it lets attractions with sufficient samples and reliable estimates account for most of the perception level at the county scale. For counties that contain no attraction meeting the threshold, we exclude them from the sample of the coupling-coordination analysis.

The third level moves from the spatial unit to the input of the coupling-coordination model. The county-level tourist sentiment perception score obtained through the aggregation above ranges from 0 to 100, and it serves as the only core indicator of the tourist perception subsystem. After range standardization to the interval [0,1], this score directly enters the coupling-coordination model as the comprehensive development index U_2 of that subsystem. One point deserves clarification here. The tourist perception subsystem is a single-indicator system, and it couples with the spatial differentiation subsystem of tourism attractions, which we synthesize from multiple weighted indicators. Such a design remains consistent with the measurement orientation of this study, since we build a quantitative proxy for tourist perception from the sentiment valence of online reviews, rather than a multidimensional evaluation system that covers cognition, emotion, and behavioral intention. The standardization formula is as follows.

$$U_{2,k} = \frac{S_k - S_{\min}}{S_{\max} - S_{\min}}$$

where $S_{\min}$ and $S_{\max}$ denote the minimum and the maximum sentiment perception scores among all counties that we include in the analysis.

3.3.3. Geographical Detector

The geographical detector is a spatial analysis tool for exploring the spatial heterogeneity of a single variable and the spatial association between two variables. It identifies the explanatory power of an independent variable, expressed as the q value, for the spatial differentiation pattern of a dependent variable, and it does not establish a causal effect in the strict sense. The method assumes no linearity among variables, and remains immune to multicollinearity [65]. Its calculation formula appears as follows.

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2} = 1 - \frac{SSW}{SST}$$

where N_h is the sample size of subregion, σ_h is the sample variance of subregion, and q denotes the explanatory power of the independent variable X for the dependent variable. The q statistic of the geographical detector requires categorical independent variables, so we must discretize the eight continuous driving factors into strata before they enter the analysis. The choice of discretization scheme directly affects the calculated q values, and we therefore specify the parameter settings from three aspects, namely, the classification method, the number of strata, and the comparison among schemes. (1) This study adopts the Jenks natural breaks classification as the baseline discretization method. This method relies on the numerical distribution of the data itself, and determines the class breaks through an iterative algorithm that minimizes within-class variance and maximizes between-class variance. Counties within the same stratum, therefore, show high homogeneity on a given factor, while different strata differ markedly from each other, and this logic fits closely with the core purpose of the geographical detector, which identifies spatial stratified heterogeneity. The equal-interval method suffers heavily from extreme values, and the quantile method forces each group to hold an equal number of samples, but may split natural clusters. By contrast, the natural breaks method suits the data characteristics of

Xinjiang better, since factor values vary widely across its counties and their distribution stays unbalanced. (2) We set five strata as the baseline scheme, and three considerations support this choice. First, the sample size constrains the design, because this study covers 86 county-level units in total, and a five-stratum classification leaves roughly 17 samples per stratum, which keeps enough observations within each stratum for a stable estimate of the within-stratum variance. Second, the scheme balances discrimination. Too few strata, such as three, would compress the spatial variation information of a factor and weaken the discriminating power of the q value, whereas too many strata, such as seven or more, would leave some strata with very few samples and make the variance estimate unstable. Third, the scheme follows the convention of comparable research, as most existing geographical detector studies at the county scale also adopt a five-stratum classification. (3) To examine how sensitive the q values remain to the discretization scheme, we additionally design several alternative schemes for comparison. One group replaces the classification method, and here we re-discretize the eight factors with the equal-interval method, the quantile method, and the K-means clustering method with k equal to 5. The other group replaces the number of strata, and here we test four, six, and seven strata under the natural breaks method. Seven alternative schemes in total compete with the baseline scheme, which combines natural breaks with five strata, and we assess the robustness of the results along three dimensions, including the stability of the factor q value rankings, the fluctuation range of the q values, and the consistency of core-factor identification. Section 4.4 reports the specific test results in the robustness analysis.

In addition, one point still deserves clarification. We standardized all factors with the range method before discretization, so every factor value falls within the interval $[0, 1]$, and the discretization operates on these standardized values. The fragmentation of tourism resources works as a negative indicator, yet we already adjusted its standardization direction during the preprocessing stage, and we therefore applied no extra treatment to it during discretization.

4. Results

4.1. Tourist Sentiment Perception Scores

The tourist sentiment perception scores of tourism attractions in Xinjiang show a markedly unbalanced spatial distribution (Figure 3). The highest scores across the region concentrate in Urumqi, and its attractions lead the whole region in the level of tourist sentiment evaluation. Ili Prefecture, including Yining, together with Kashgar, Korla, and Karamay, forms the secondary high-value areas, since these central urban districts of each prefecture serve as several regional growth poles of tourist sentiment perception. The sub-high-value areas basically surround the above core cities in a concentric pattern, and the level of tourist sentiment perception declines in gradients as the distance from these core cities increases. By contrast, the peripheral counties of southern Xinjiang, the remote pastoral areas of northern Xinjiang, and some scattered attractions in eastern Xinjiang receive relatively low scores, and their gap from the core cities in sentiment evaluation remains fairly obvious.

The spatial differences in these scores reflect, from the sentiment dimension, the spatial pattern of how tourists perceive their visiting experience at various attractions. Attractions in high-score areas generally receive positive feedback across multiple topics in their sentiment evaluations. Tourists widely recognize the ornamental value of the core landscape resources, and the services and supporting facilities throughout the whole visiting process also earn fairly stable positive comments. Within the review texts, the sentiment tendency toward topics such as landscape quality, service quality, and the completeness of supporting facilities remains mainly positive, while negative perceptions

account for a very small share, and these conditions together support a high comprehensive sentiment score. Attractions with sub-high scores mostly cluster around the core cities, and they rely on distinctive natural landscapes or folk culture sites as their main attractiveness, so their own resource endowments hold a differentiated advantage. Their short distance from urban districts further allows tourists to complete accommodation, catering, and other supporting consumption in the city, which effectively shares the pressure of facility provision that these attractions would otherwise bear alone, and the sentiment evaluation of the basic visiting experience therefore stays stable. As for attractions in remote areas with lower scores, the negative sentiment of tourists mainly arises from a strong sense of trip attrition. Remote sites commonly require long round-trip travel time, and the effective visiting duration accounts for only a small proportion of the journey, so travel fatigue easily amplifies minor shortcomings during the visit. Some of these attractions also lack refined operation and maintenance, and such multiple weaknesses in experience jointly pull down the comprehensive sentiment perception score of tourists.

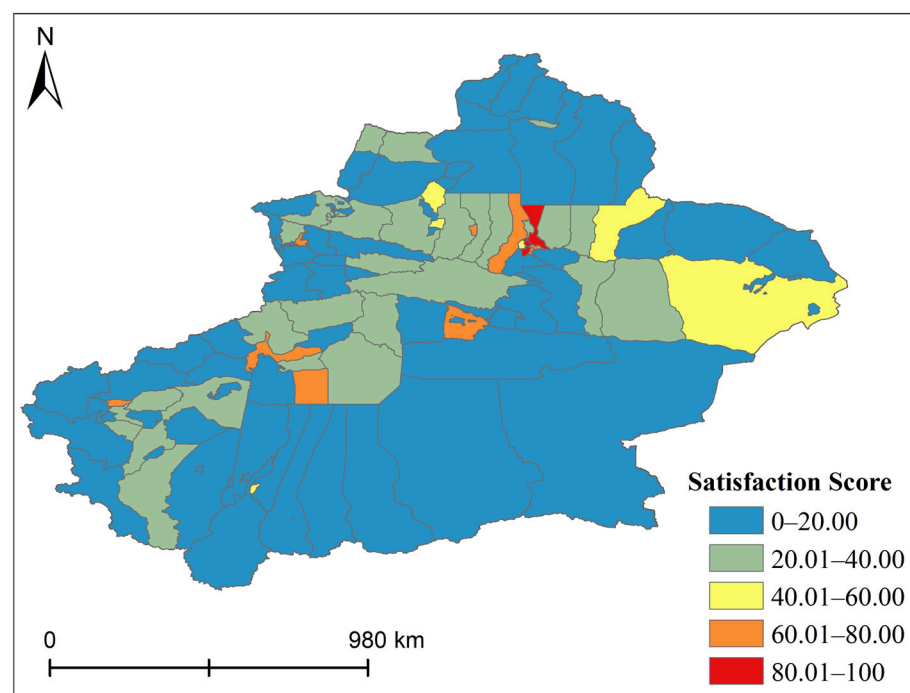


Figure 3. Spatial distribution of tourist sentiment perception scores of tourism attractions in Xinjiang, based on RoBERTa-wwm sentiment analysis, with scores ranging from 0 to 100.

4.2. Coupling-Coordination Analysis Between Tourist Sentiment Perception and the Distribution of Tourism Attractions

We applied the coupling-coordination model to measure how far the spatial distribution of tourism attractions in Xinjiang and tourist sentiment perception develop in step. Coupling coordination differs markedly across the region, and favors northern Xinjiang overall (Figure 4). Most research units reach a coupling-coordination degree above 0.5 and therefore fall within the coordinated range, and the units with high coordination concentrate in northern Xinjiang. Backed by relatively complete tourism facilities and a mature market, most areas there match the scale of their attraction layout with the level of sentiment perception, and the two systems interact strongly. Some remote areas of southern and eastern Xinjiang, by contrast, fall below 0.5, and remain uncoordinated, because the distribution of attraction resources and the improvement in sentiment perception have not yet formed effective mutual feedback.

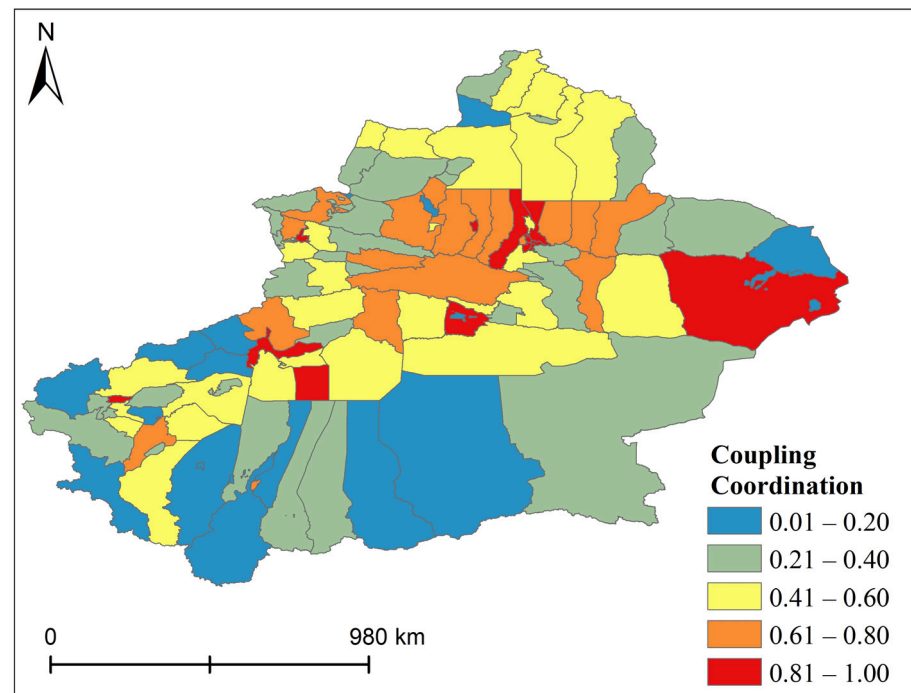


Figure 4. Spatial distribution of the coupling-coordination degree between the spatial differentiation of tourism attractions and tourist sentiment perception in Xinjiang, measured by the coupling-coordination model, with values ranging from 0 to 1.

Units whose coupling-coordination degree exceeds 0.7 cluster in Urumqi and in the attraction belt that visitors can reach on a same-day round trip from the city, which covers the suburban districts and the neighboring counties. This belt is the core supply block of Xinjiang, since it carries the highest attraction density and the most complete type system in the region, and it also concentrates the highest tourist perception scores. The scale effect of spatial clustering and the improvement in the level of tourist sentiment evaluation therefore reinforce each other. Densely distributed attractions share the transport, accommodation and catering resources of Urumqi, which lightens the operation and maintenance burden on any single site, while consistently high sentiment ratings draw larger tourist flows into the belt. Attraction development and service quality thus upgrade through positive mutual feedback, and the belt finally shows the highest level of coupling coordination in Xinjiang.

The correspondence between the distribution scale of attractions and tourist perception scores shows that growth in attraction numbers and improvement in the level of tourist sentiment perception do not follow a simple linear positive relation, and a larger number of attractions does not necessarily raise tourist perception scores. Only the area around Urumqi achieves joint growth in the two dimensions. The northern part of northern Xinjiang, which lies to the north of Urumqi, holds dense attractions and outstanding natural tourism-resource endowment, and ranks among the areas with the largest attraction scale in the region, yet its tourist perception scores have not risen with the expansion of attraction numbers. Its overall coupling-coordination degree stays at a medium level, so it has not formed a highly coordinated pattern that matches its resource scale. Expansion in attraction numbers and spatial clustering, therefore, hardly ever converts into an advantage in tourist sentiment perception on its own. Once supporting services, operation management and product upgrading lag behind the pace of resource exploitation, a supply–demand mismatch occurs, in which resource density stays high while sentiment evaluation remains flat, and this mismatch restricts further improvement in the coupling coordination between the two systems (Figure 5).

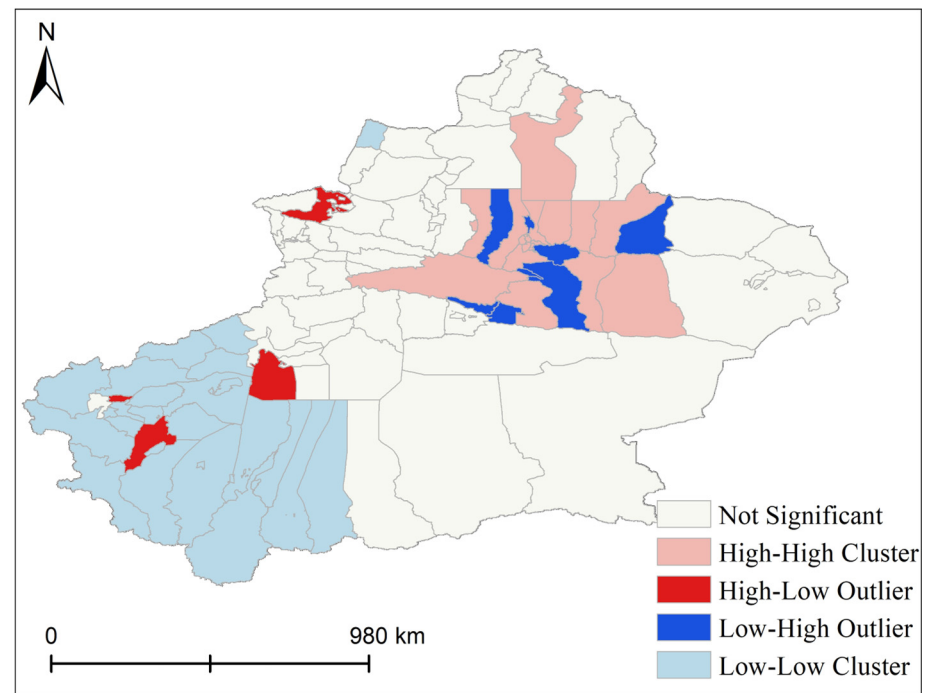


Figure 5. Distribution pattern of tourism attractions.

4.3. Influencing Factors and Driving Paths

This study takes the coupling-coordination degree between the spatial differentiation of tourism attractions and tourist perception in Xinjiang as the dependent variable. Drawing on eight driving factors from three dimensions, namely, the land resource background, the development of the tourism industry, and the socioeconomic support, we discretize each factor into five strata with the natural breaks method, and we then apply the geographical detector to identify quantitatively how strongly each factor acts on the level of coupling coordination, and through what logic it exerts this influence (Figure 6). IC ranks first in spatial explanatory power, so it is the factor most strongly associated with the spatial differentiation of the coupling-coordination level. ITD and CCI constitute the second tier, and both hold substantial explanatory power for the spatial pattern of supply–demand coordination. ITD and FTR occupy the middle tier, where they play a structural role in shaping the coupling-coordination pattern. EDL and PD hold the lowest explanatory power, so their direct driving effect on the coupling of the two subsystems remains limited.

IC carries the highest explanatory power among all factors, and plays a decisive role in the coordinated development of the tourism supply-and-demand system in Xinjiang. The region covers a vast territory and its attractions lie far apart, so transport networks and public service facilities form the core link that connects tourism resources and carries the movement of tourists. The coverage of such infrastructure acts on both the spatial development of attractions and tourist sentiment perception. On the supply side, well-developed infrastructure lowers the threshold for exploiting remote attractions, supports the orderly use of tourism resources and the optimization of spatial layout, and drives scattered attractions toward linked development. On the demand side, transport and service facilities with high coverage cut the commuting loss and the time cost that tourists bear, ease the fatigue of long-distance travel, and directly improve the smoothness and the comfort of the visit.

The development of sightseeing attractions alone only expands the spatial scale, and it hardly sustains any continuous rise in the level of tourist sentiment perception. By contrast, comprehensive development that covers diverse formats such as distinctive catering,

boutique accommodation, cultural experience, and cultural creative leisure extends the tourism industrial chain and enriches both the layers of the visit and the dimensions of the experience. In theory, such development helps lengthen the stay of tourists, raise their satisfaction and revisit intention, and win more positive feedback in sentiment evaluations. The clustering of diverse formats also upgrades supporting tourism and services as a whole, optimizes the spatial function structure around attractions, and pushes tourism attractions from isolated resource points toward comprehensive tourism destinations, which promotes the value conversion of the spatial development.

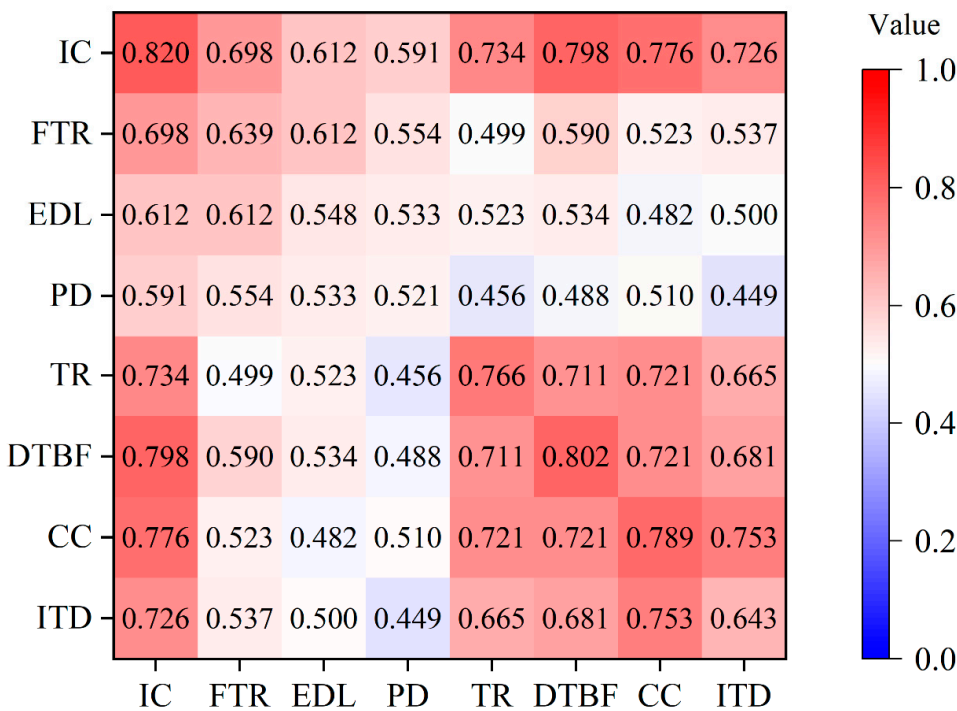


Figure 6. Results of factor interaction.

CCI acts as a fundamental natural factor in the coordination between tourism supply and demand in Xinjiang. The region spans several climatic zones, and conditions differ markedly between southern and northern Xinjiang and between mountains and basins, which determines the suitable visiting season and the market carrying potential of regional tourism. Areas with a higher CCI enjoy a longer annual window for visits, so they sustain a more continuous inflow of tourists and a more refined operation of attractions. These conditions favor the deep exploitation of tourism resources and their routine maintenance, and they secure a stable and comfortable visiting experience, which helps the supply-and-demand system build long-term coordination. Areas with harsh climatic conditions show strong seasonality, instead. Investment in attraction development there faces a long payback period and difficult maintenance, and tourists lower their ratings under extreme weather, so natural conditions constrain both sides of the system and the coupling-coordination level rises only slowly.

Moderate tourism development improves the reception service functions of attractions, raises both the scale and the quality of regional tourism supply, matches the growing demand of tourists, and therefore pushes the two sides to upgrade together. A higher ITD, however, does not necessarily raise the coupling-coordination level. Once development relies on extensive quantitative expansion and pursues a larger number of attractions while neglecting service quality and supporting facilities, a mismatch appears in which attraction density stays high and sentiment evaluation remains flat, and this mismatch

restricts coupling coordination, instead. The northern part of northern Xinjiang holds many scenic areas, yet its coupling-coordination level has not reached a high position, which shows directly that development intensity and experience quality do not advance in step. Only refined and quality-oriented development builds a positive spatial association with the level of supply-demand coordination.

EDL and PD rank last in spatial explanatory power, and both show a limited association with the spatial differentiation of the coupling-coordination level. This result fits the tourist source structure and the development mode of tourism in Xinjiang. Xinjiang serves as a nationwide destination, so its tourists come mainly from other provinces, and the local resident population supports the tourism market only weakly, which means that PD cannot turn directly into market momentum for tourist sentiment perception. Tourism development in the region also shows strong policy guidance and clear external capital injection, and the exploitation of high-quality tourism resources does not fully depend on the local economic base. Many areas with an ordinary economic level but outstanding resource endowment still reach a fairly high degree of tourism development, so the local economy explains the coupling of supply and demand relatively weakly.

4.4. Robustness Test

The tourist perception score is the core input of the coupling-coordination analysis, so the sentiment weights used to measure it may affect the conclusions. We therefore conducted a sensitivity analysis that replaces the weight scheme, comparing the benchmark scheme, which assigns 1 to positive sentiment, 0.5 to neutral sentiment and 0 to negative sentiment, with three alternatives. The first alternative weakens the neutral category with weights of 1, 0.3 and 0, which reduces the contribution of neutral sentiment to the composite score and sharpens the contrast between positive and negative sentiment. The second strengthens the neutral category with weights of 1, 0.7 and 0, which lets evaluations without a clear tendency exert more influence on the composite score. The third adopts a symmetric valence with weights of 1, 0 and -1 and maps the result linearly onto a range from 0 to 100, so positive and negative sentiment carry symmetric weights while neutral sentiment sits at a middle zero point that contributes nothing.

We recalculated the tourist perception score of each attraction under the four weight schemes above, repeated the measurement of the coupling-coordination degree and the factor-detection analysis, and then tested the stability of the core conclusions along four dimensions.

First, we examined the ranking consistency of the tourist perception scores. Taking the attraction scores under the benchmark scheme as the reference, we calculated the Spearman rank correlation coefficients for the three alternative schemes, which reach 0.96, 0.94 and 0.91 respectively (and are all significant at $p < 0.001$). The rankings of the attraction perception score, therefore, stay highly consistent across the weight schemes, and adjusting of the weights does not change the relative pattern of the level of sentiment perception among the attractions.

Second, we examined the stability of the spatial pattern of the coupling-coordination degree. Across the four schemes, the Pearson correlation coefficients between the three alternative schemes and the benchmark scheme reach 0.97, 0.95 and 0.90, respectively, and are all significant at $p < 0.001$. Highly coordinated units always cluster in Urumqi and its surroundings, whereas the remote areas of southern and eastern Xinjiang remain uncoordinated. The overall pattern, which runs high in the north and low in the south, with the core region leading, holds under all four schemes and shows no fundamental reversal.

Third, we examined the robustness of the factor ranking. IC ranks first in explanatory power under every scheme, RTF and CCI always occupy the second tier, and EDL and

PD always rank last. Moreover, the q value of each factor fluctuates by no more than 0.05 across the different schemes, so the ranking of the factors shows no substantive change.

Fourth, we examine the robustness of the discretization scheme in the geographical detector. Since the q value may stay sensitive to the way we discretize the independent variables, this study further tests how stable the factor-detection results remain across different classification methods and numbers of strata. For the alternative classification methods, the Spearman rank correlation coefficients of the q values of the eight factors reach 0.93, 0.91, and 0.95 under the equal-interval method, the quantile method, and the K-means clustering method respectively, when we compare each of them with the baseline scheme that combines natural breaks with five strata, and all three coefficients stay significant at the level of $p < 0.001$. Infrastructure coverage firmly holds the first place in explanatory power under every scheme, while the richness of tourism formats and the climate comfort index always fall into the second tier, and the regional economic development level and population density, always rank at the bottom, so the ranking of factors undergoes no substantial change. For the alternative numbers of strata, the Pearson correlation coefficients between the baseline five-stratum scheme and the four-, six-, and seven-stratum schemes under the natural breaks method reach 0.96, 0.97, and 0.94, respectively. The maximum fluctuation of the q value of each factor stays within 0.06, and the identification of the core driving factors remains completely consistent. These tests indicate that the core conclusions of the geographical detector in this study stay insensitive to the choice of discretization method and the number of strata, and they therefore possess good robustness.

The sensitivity analysis above shows that the core conclusions of this study remain stable under reasonable alternative sentiment-weight schemes and discretization settings. The spatial pattern of the tourist perception scores, the contrast in coupling coordination between the north and the south, and the leading role of IC all hold, so the results are robust.

5. Discussion

As the culture and tourism industry enters a stage of high-quality development, tourist perception has become a core yardstick for judging the quality of that development. We therefore draw on multi-source tourism location data and platform review texts, and apply RoBERTa-wwm sentiment analysis, the coupling-coordination model and the geographical detector, to examine how the spatial differentiation of tourism attractions couples with tourist perception and what shapes their spatial association.

Early studies of tourism spatial differentiation in China and elsewhere focused on the distribution pattern, the clustering features and the supply efficiency of tourism resources, and later work gradually brought in the perspective of tourists [66]. Most of that work evaluates the experience of a single destination or the perception differences within one attraction, and few studies treat tourist perception as an independent system and couple it systematically with the overall tourism spatial pattern of a region [67,68]. Research in China has long taken A-level attractions as its object, and has explained spatial differentiation mainly through supply-side dimensions such as resource endowment, economic level and traffic conditions [69]. Its treatment of tourist perception remains confined to evaluations of a single city or a single attraction, and the demand-side perception system has not yet entered the analytical framework of tourism spatial differentiation, so the two-way interaction between the two sides still lacks systematic quantitative verification [70]. The two lines of work nevertheless agree that tourist perception is a core dimension for measuring the quality of tourism development, and that improving the tourist experience is the final goal of tourism spatial development [71]. Existing studies mostly treat tourist perception as a subsidiary output of scenic-area development [72]. We, instead, treat it as one of two

equal systems, alongside the spatial differentiation of attractions, and focus on the spatial coupling between them; this offers a new empirical perspective on the interaction between tourist perception and the spatial pattern of tourism attractions.

Mainstream research on the driving mechanism of tourism spatial differentiation generally regards the quantity of tourism resources, the regional economic development level and the population size as the core forces behind tourism development [73]. It assumes, by default, that a rise in attraction density and an expansion of resource scale bring a synchronous growth in tourism benefits and tourist experience, so it often treats the expansion of attraction numbers as the core path of regional tourism development [74]. Studies of the densely populated central and eastern regions of China, where infrastructure is mature, have widely confirmed this view [75]. Our results differ from the existing mainstream understanding in two obvious respects. The first respect concerns the hierarchy of spatial explanatory power among the factors. IC is the factor most strongly associated with the spatial differentiation of the coupling-coordination level, while ITD ranks second, and EDL and PD, factors foregrounded in traditional scholarship, demonstrate the weakest spatial explanatory power. A second divergence concerns the relationship between resource scale and experience quality. Attraction growth and perception gains do not move in tandem in our data. The northern part of northern Xinjiang concentrates attractions densely, yet perception scores there do not rise commensurately, indicating that expanding the number of attractions alone does not translate into an experience advantage [76]. These divergences may be attributable to differences in the endowment features of the study areas. Existing studies predominantly examine inland regions in central and eastern China, where a sound infrastructure base and a sufficient local source market allow economy and demographic factors to support tourism development substantially [77]. Xinjiang, by contrast, functions as a large-scale tourism destination, and the observed spatial pattern suggests that accessibility constraints arising from spatial distance may constitute a prominent factor shaping the coordination between tourism supply and demand. Since Xinjiang's source market consists primarily of extra-regional tourists, the comparatively weak spatial explanatory power of local EDL and the population size is consistent with the interpretation that the local economy and population provide relatively limited direct support for the coordination. Meanwhile, scenic areas cluster densely in the northern part of northern Xinjiang, yet perception scores and coupling coordination there do not rise in step. This pattern suggests that when scenic-area expansion outpaces the development of supporting facilities and business formats, resource scale and experience quality fall out of alignment [78]. It should be pointed out that all of the foregoing explanations are derived from the spatial association features revealed by cross-sectional data, and that they therefore represent reasonable interpretations consistent with the observed pattern, rather than conclusions validated by rigorous causal inference. Once future research incorporates time-series data and micro-level tracking of tourist behavior, these proposed mechanisms can be tested more rigorously. This finding also implies that, beyond a certain stage of tourism development, a quality-oriented path that addresses infrastructure gaps and diversifies business formats may achieve better supply–demand coordination than a strategy that relies solely on increasing attraction numbers.

This study adopts the perspective of tourist experience, and takes Xinjiang as a representative case to reveal the coupling mechanism and driving paths between the spatial differentiation of tourism attractions and tourist perception. The first contribution lies in enriching the analytical dimensions of research on tourism spatial differentiation from a demand-side perspective, thereby promoting deeper integration between supply-side pattern analysis and demand-side experience studies. By converting individual tourists' experiential evaluations into quantitative indicators with spatial attributes, this study effec-

tively bridges the macro spatial pattern with micro-level market feedback, and broadens the observational scope of research on tourism spatial differentiation. The second contribution lies in revealing the core spatial association features of the coupling between tourism supply and demand in a large-scale heterogeneous region. This study challenges the linear assumption regarding the relationship between scenic-area scale and tourist experience quality, finding that IC and RTF are the variables most strongly associated with the level of supply-and-demand coordination, while the regional economy and the population size hold relatively limited spatial explanatory power. Furthermore, this study identifies a spatial pattern in which growth in the number of tourism scenic areas does not necessarily produce a synchronous rise in tourist sentiment perception, which provides new empirical evidence for deepening the understanding of how the spatial differentiation of tourism takes shape.

Several limitations qualify these findings. The first concerns sample representativeness and selection bias across platforms. Tourist perception data in this study are drawn from the user-generated content on two platforms, Trip and Rednote. Although the sample is large and spatially comprehensive, the two platforms differ systematically in the demographic characteristics and behavioral preferences of their users. Trip operates as an online travel booking and review platform whose active users consist mainly of young and middle-aged independent tourists with considerable consumption capacity. Their reviewing behavior typically occurs as post-visit order feedback, and focuses on standardized dimensions such as landscape quality, ticketing service and supporting facilities. Rednote, by contrast, is a lifestyle-sharing platform with a younger, disproportionately female, user base. Content on Rednote blends travel documentation with social sharing, emphasizing check-in experience, visual presentation and emotional expression, while also providing broader coverage of trending attractions and niche destinations. Both platforms share a common limitation, in that they inadequately capture the experience perception of group tourists, middle-aged and elderly tourists, and local leisure tourists. Group tourists seldom post independent reviews on these platforms, middle-aged and elderly users exhibit lower platform-adoption rates and weaker willingness to contribute content, and the visiting behavior of local leisure tourists is frequently under-captured by platform data. In addition, the two platforms display selection bias in their coverage of attractions and distribution of reviews, Trip provides more systematic coverage of formally rated A-level scenic areas, while Rednote covers emerging internet-famous check-in spots and niche destinations more fully. Review volumes and evaluative tendencies for the same attraction may therefore differ between the two platforms, and cross-platform data fusion may introduce systematic bias. Collectively, these platform-specific demographic and behavioral biases may cause the tourist perception scores in this study to skew somewhat toward the experience demands of young and middle-aged independent tourists, under-representing the experiences of other tourist segments.

Review counts are also uneven across attractions and spatial units. Tourist perception scores in this study are constructed by aggregating platform reviews of every attraction; however, review volumes vary markedly across attractions and spatial units. Popular attractions and core tourism cities receive far more reviews than attractions in remote areas, and some peripheral counties yield a comparatively limited number of valid reviews. Although a minimum threshold of 30 reviews per attraction was applied, uneven review counts may still compromise the precision and stability of the derived scores. Attractions with larger review volumes yield more robust estimates, whereas those with fewer reviews are more susceptible to fluctuation. This imbalance closely mirrors the spatial pattern of tourist flows, and may, consequently, amplify perceived differences in perception scores between core and peripheral areas.

Automatic sentiment classification introduces a further source of uncertainty. This study employs the RoBERTa-wwm model, fine-tuned on domain-specific data, to perform automatic sentiment classification of tourist review texts. Although the model achieves an overall accuracy of 89.3% and a macro-averaged F1 score of 85.9% on the test set, automatic classification retains a non-trivial misclassification rate, particularly for boundary samples situated between neutral and mildly positive or negative sentiment. Moreover, complex linguistic phenomena that appear widely in tourism reviews, including irony, sarcasm, implicit expression and internet slang, may further affect the accuracy of the sentiment recognition of the model. Classification errors propagate through the measurement of the composite score into the subsequent coupling-coordination analysis, and thereby introduce distortions into the research conclusions.

The coupling-coordination analysis is in turn sensitive to indicator construction and weighting. The measurement of the coupling-coordination degree depends on the construction of the indicator system and allocation the weight across the two subsystems of the spatial differentiation of tourism attractions and tourist perception. Within the spatial differentiation subsystem, the selection and the weighting of indicators may affect the measurement of the comprehensive development index. Within the tourist perception subsystem of, the scheme that converts sentiment probabilities into a hundred-point scale, assigning values of 1, 0.5, and 0 to positive, neutral, and negative sentiment, respectively also involves a degree of subjective discretion. Sensitivity analysis confirms that the core conclusions remain robust under three alternative weight schemes. Nevertheless, the design of the indicator system, the subsystem weights of 0.5 and 0.5, and the choice of standardization method may still affect the absolute coupling-coordination values and the resulting spatial classification.

A further constraint is that the analysis depicts a static pattern and lacks a dynamic evolutionary perspective. This study mainly draws on cross-sectional data from 2025 to characterize the current state of coupling coordination between the spatial differentiation of tourism attractions and tourist experience in Xinjiang, and does not incorporate time-series data over a longer span for longitudinal tracking. Cross-sectional analysis can present the spatial association features at a single point but cannot capture the temporal evolution of the coupling-coordination relationship and is ill-suited to rigorous causal inference. In fact, the relationship between tourism supply and tourist experience is dynamic. It evolves continuously as transport infrastructure improves, scenic area products are updated, market demand shifts, and the policy environment changes. A type of spatial mismatch at one point in time may therefore transfer to another type several years later. For example, an area characterized by high attraction clustering but low perception scores may shift toward the type that combines high clustering with high perception once it fills the gaps in its supporting facilities. These dynamic features require destination management to move from static blueprint planning toward adaptive management, establishing a closed-loop mechanism that integrates continuous monitoring, dynamic assessment, and timely adjustment, enabling managers to reallocate resources flexibly in response to real-time changes in supply–demand coupling. Once future research incorporates panel data across multiple years, it can further reveal the dynamic evolutionary trajectory of the coupling-coordination pattern and the temporal changes in the driving mechanisms, which will provide more solid empirical support for adaptive destination management. In addition, the calculation of the q value in the geographical detector depends on the discretization scheme of continuous independent variables. Although this study verifies the robustness of its core conclusions through the comparison of multiple schemes, the choice of the classification method and the number of strata may still affect the precise value of the q

statistic for an individual factor to some extent, and this remains an inherent limitation of the geographical detector method itself.

Finally, the particularity of the study area constrains the broader applicability of the conclusions. Xinjiang is a large-scale border tourism destination with distinct features, including a vast territory, a wide spatial span between attractions, a source market that depends mainly on extra-regional tourists, and an uneven spatial distribution of infrastructure. These features explain why IC and RTF play prominent roles in the coupling between supply and demand, while the regional economy and the population size hold relatively limited direct explanatory power. This finding differs clearly from the conclusions reached in studies of the densely populated central and eastern regions with mature infrastructure. This divergence suggests that the driving logic of the coupling between tourism supply and demand carries significant regional heterogeneity. Consequently, the conclusions and planning recommendations of this study mainly apply to large-scale border destinations that rely on non-local source markets and share endowment features similar to those of Xinjiang. Researchers should exercise caution in extrapolating these conclusions to mature, densely developed tourism regions in central and eastern China or to small-scale tourism destinations, and should make appropriate adjustments based on the specific region's resource endowment, source market structure, and infrastructure conditions.

Future research will address the above limitations along several fronts. Combining multiplatform data with offline surveys to improve the sample structure, introducing multi-level models and uncertainty propagation analysis to quantify the effect of sentiment classification errors, constructing long time-series panel data for dynamic and causal analysis, and conducting multi-case comparisons to evaluate the generalizability of the conclusions.

6. Identification of Spatial Mismatch Types and Differentiated Planning Strategies

To further enhance the practical applicability of the research results, this study develops a four-quadrant analytical framework based on the two-dimensional combination of the clustering degree of attractions and the level of tourist perception. This framework classifies the spatial units across Xinjiang into four types of spatial matching, and it accordingly proposes differentiated strategies for tourism planning and land use planning. The clustering degree of attractions relies on the number of tourism attractions per unit area as its indicator, and the level of tourist perception relies on the comprehensive score of the tourist perception subsystem in the coupling-coordination analysis, which we derive from the sentiment tendency scores. We take the median value of the whole Xinjiang region as the classification threshold for both of them.

Type one covers the combination of high clustering and high perception, and we name it the collaborative optimization type. Urumqi and the surrounding areas within short-distance reach represent this type, where the density of attractions stays high, the level of tourist sentiment perception remains excellent, and the supply-and-demand system maintains coordination at a high level. For these areas, tourism planning should reorient its focus from scale expansion toward quality cultivation. Planners should restrain the homogeneous development of new attractions, encourage existing scenic areas to upgrade their products and diversify their business formats, and promote the transition from conventional sightseeing offerings to products that provide deep experiential engagement and cultural immersion. Land use planning should prioritize the allocation of land for tourism supporting facilities and public services, optimize the layout of transport connections and slow-traffic corridors around scenic areas, and establish reasonable boundaries for ITD, so as to prevent excessive commercialization from eroding landscape integrity and experience quality. Meanwhile, these areas can leverage the radiating and catalytic role of core cities to

guide the coordinated improvement of surrounding areas with low perception, through the organization of tourism routes and the diversion of source markets.

High clustering with low perception characterizes the mismatched type. Parts of northern Xinjiang fall into this quadrant. Attraction resources are concentrated and natural endowments are outstanding, yet perception scores and coupling coordination failed to keep pace with the growing number of scenic areas. Resource density is high, while sentiment evaluation, as reflected in visitor evaluations, remains flat. For these areas, the central task of tourism planning should be to fill service-facility gaps and refine operational management standards. Planners should first improve the transport connectivity between scenic areas and the service facilities along travel corridors, thereby addressing the time losses caused by long journeys and compressed visit durations. They should also promote the upgrading of single-function sightseeing scenic areas into comprehensive destinations that integrate scenic areas with accommodation, catering and cultural experience, extending visitors' length of stay and expanding the consumption chain. In addition, standardized operational and management frameworks should be strengthened for scenic areas, and the professional competence and emergency-response capacity of service personnel should be raised. Land use planning should allocate land for tourism facilities sensibly. Within the ecological protection of the red line, it should give priority to trunk transport lines, tourist service centers and supporting accommodation. Land consolidation and mixed functions can further raise the efficiency and value of land around scenic areas.

Low clustering with high perception characterizes the latent-potential type. This type appears predominantly in areas endowed with distinctive resources that remain lightly developed; the number of attractions is limited, yet tourists sentiment evaluates the existing attractions highly, which indicates that resource quality holds an advantage, while the scale of development lags behind. For these areas, tourism planning should adhere to the principle of letting quality lead quantity, and pursuing measured, incremental development. Within the carrying capacity of the ecological environment, planners should advance the tourism-oriented development of high-quality resources and cultivate new growth poles of attractions. They should also build on the brand recognition of the existing high-perception attractions to extend the tourism industry chain, develop distinctive cultural creative products and immersive-experience programs, and thereby convert the strength of individual sites into a regional competitive advantage. Land use planning should reserve a moderate amount of land for future tourism development, and thereby provide spatial support for the subsequent development of attractions and the construction of supporting facilities. At the same time, development intensity and construction style should be strictly controlled to prevent low-quality, homogeneous development from undermining the resource base that visitors currently regard so highly.

Low clustering with low perception characterizes the underdeveloped type. This type appears mainly in the peripheral counties of southern Xinjiang and the remote pastoral areas of northern Xinjiang, where attractions remain scarce and the tourist perception scores stay low, so both sides of the supply-and-demand system remain at a relatively low level of development. For these areas, tourism planning should adopt a strategy of targeted breakthroughs pursued incrementally. Rather than dispersing efforts across the entire area, planners should first identify sites with differentiated resource endowments and a baseline level of accessibility, and cultivate them as regional tourism growth poles. These areas should also strengthen the connection to adjacent high-perception tourism circuits, enabling them to grow by drawing on external strengths through shared visitor markets and joint development initiatives. Land use planning should incorporate tourism development into the broader co-ordination of territorial spatial planning and, on the premise of prioritizing ecological conservation, delineate areas suitable for tourism development in a rational

manner, avoiding both the waste of resources and the ecological damage that results from uncoordinated expansion. Planners should further attend to the alignment of tourism development with rural revitalization and characteristic urbanization, using tourism as a lever to drive local employment, increase household incomes, and improve public service provision in local communities.

The four-quadrant classification framework above translates the abstract results of the coupling-coordination analysis into operable types of spatial planning, and it therefore provides differentiated bases for decisions on the tourism-development positioning and the land use strategies of different areas. It should be emphasized that the four types are not static. As transport conditions improve, as scenic areas upgrade their operations, and as market demand changes, the type to which any given area may shift changes dynamically. This fluidity requires tourism planning and land use planning to maintain flexibility and adaptability over time.

7. Conclusions

This study takes Xinjiang as a representative case, constructs an analytical framework that couples the two systems of the spatial differentiation of tourism attractions and tourist perception, and systematically reveals the spatial regularities and the factor-association features underlying the coordination between tourism supply and demand in a large-scale, highly heterogeneous region. The core conclusions run as follows. First, the spatial differentiation of the level of sentiment perception shows a marked dependence on central cities, and the spatial association between tourism resource endowment and the level of tourist perception stays weaker than that between spatial accessibility and comprehensive service-provision capacity. The spatial pattern of tourist perception does not fully match the distribution of tourism resources. Instead, it corresponds closely to the service radiation range of regional central cities, and it evolves in concentric circles that lead outward from a strong core and decline in gradients. Spatial accessibility and the capacity of comprehensive service supply, therefore, act as the fundamental constraints that shape the pattern of tourist sentiment perception at a large regional scale. The second point is that no natural linear positive correlation exists between the scale expansion of tourism attractions and the improvement in tourist sentiment perception, since the coupled and coordinated development of the two shows obvious asynchrony. The clustered growth in the number of scenic areas only provides a resource base for tourism development. Once the supply of supporting services and business formats lags behind the pace of resource exploitation, the spatial pattern often reveals a mismatch between the scale of resources and the level of sentiment perception on the supply-and-demand sides. Only when spatial development and the quality improvement in sentiment perception advance at the same pace, can a region achieve high-level coordinated development between tourism supply and demand. Third, the factor-association features of the supply–demand coupling relationship in Xinjiang display pronounced regional heterogeneity and diverge clearly from findings reported in existing studies of densely populated regions in central and eastern China. Among the eight driving factors that this study includes, IC and RTF hold the highest spatial explanatory power measured by the q value, and they show the most prominent positive spatial association with the level of coupling between supply and demand. Conventional factors such as EDL and PD hold relatively low spatial explanatory power. Furthermore, relative to local market factors, the accessibility constraint shows a stronger negative spatial association with the level of supply-and-demand coordination, a pattern suggesting that accessibility conditions may constitute a binding constraint that warrants particular attention in efforts to achieve coordinated supply–demand development in large-scale border tourism destinations. It should be noted that all the conclusions above rest on

the spatial association analysis of cross-sectional data, and that they therefore reflect the statistical strength of the association between the factors and the coupling-coordination level, rather than driving effects that causal inference has strictly verified.

In addition, it should further be emphasized that the coupling relationship between tourism supply and tourist experience is inherently dynamic, rather than a fixed, static pattern. As transport conditions improve, as products and business formats upgrade and as market demand changes, the type of spatial matching to which an area belongs may shift. Destination management, therefore, needs to transition from static planning toward adaptive management, continuously monitoring and evaluating supply–demand coupling, and adjusting development strategies and resource allocation as conditions evolve, so that tourism supply and tourist experience stay aligned over time. On the whole, in an era of high-quality tourism development, a growth path premised solely on expanding the quantity of resources is unlikely to prove sustainable. Tourism spatial development should therefore pivot toward a quality-oriented trajectory, one that places tourist experience as its core orientation and takes IC and RTF as its core support, so as to more effectively translate resource advantages into experiential advantages and, ultimately, into competitive industrial development advantages.

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